ABSTRACT

The Impact of Wildfire Smoke on Solar Electricity Generation:
An Analysis of the Western United States

by

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In recent decades, wildfire seasons have been getting longer, more costly, and more devastating. Studies have shown that the growing prevalence and size of wildfires are leading to several adverse health, economic, and environmental outcomes. This paper contributes to that literature by identifying whether or not increased smoke concentrations from wildfires are having a significant impact on solar energy production. Using monthly solar generation data from the US Energy Information Agency, PM 2.5 concentration levels from a machine learning algorithm developed by Marissa Childs and colleagues at Harvard, and climate data from the PRISM Climate Group at Oregon State University, I construct a panel data set for multiple western states from 2013 to 2020. Using a two-way fixed effects model, I find that a 1 micro gram increase in wildfire-related atmospheric fine particulate matter is associated with a .014 percent reduction in solar energy generation. That can result in a 20 to 30 percent reduction during major wildfire months. This finding is consistent with other academic studies which have found that high concentrations of airborne particulate matter can significantly reduce solar energy generation. This paper has important implications for the future of renewable energy and forest management.

CHAPTER 1

INTRODUCTION

Over the past 10-15 years, wildfires have become a growing threat in the United States, most notably in Western communities. Data from the National Interagency Coordination Center and United States Forest Service highlight a concerning trend for many Americans, especially those living out west: despite no noticable increase in the number of fires occurring each year, the average size and damage caused by wildfires has been growing steadily. Eight of the ten costliest fires in US history have occured in the past decade. Annual economic costs of these wildfires has been estimated to be in the hundreds of billions of dollars. Iglesias et al. (2022) find that these trends are significantly different from previous decades, noting a shift in fire behavior occuring around the year 2000.

Experts have pointed to a number of causes for the increasing prevalence of large wildfire events. Twentieth century fire management, which emphasized suppression to remove fire from the landscape, has reduced the resiliency of previously fire-adapted ecosystems. This has also led to a buildup of both dead and living combustable material, which increases the risk of severe fires (Stephens et al. (2009); Parks and Abatzoglou (2020)).

Anthropogenic climate change is further weakening once fire-resilient landscapes. An analysis of climate trends by Jain et al. (2021) found that global decreases in relative humidity and increases in temperature, driven by anthropogenic climate change, have significantly increased extreme fire weather conditions over one-quarter to one-half of Earth's burnable surface since 1979. Others have noted the impact of climate change on increased aridity specifically in the Western US (Zhuang et al. (2021); Parks and Abatzoglou (2020); Williams et al. (2020)).

Finally, the increase in populations living in or near these landscapes in recent decades is contributing to both the frequency and economic costs of wildfires (Radeloff et al. (2017)). Balch et al. (2016) examined the impact of human-caused wildfire incidents on trends between 1992 - 2012. They found that human-caused fires accounted for 84 percent of all wildfires during that period and 44 percent of area burned. Most notably, human-caused wildfires commonly occurred nearer to populated areas and stretched fire seasons to three times longer than lightning-caused fires.

Baylis and Boomhower (2023) studied the role that federal and state spending on wildfire suppression has played in enabling this growth. They find that most of the federal and state dollars spent fighting wildfires each year go towards protecting private homes, and this implicit subsidy has increased development in fireprone areas on average by 2.5 percent. It has increased development in the highest risk areas by more than 25 percent. The increasing severity, scope, and risks to communities posed by wildfires creates a growing need for governments and agencies to both understand and plan for the future impacts these fires will have on their communities.

One area of concern which has not been studied extensively is the potential impact of wildfire smoke on solar electricity generation. Many states, especially western states with sunny climates, are setting clean energy standards, regulations, and long-term goals which rely heavily on solar energy production. California regulators, for example, have estimated that they will need to quintuple installed solar generation capacity in order to meet their goal to be carbon free by 2045.

In this paper, I attempt to understand whether there is a significant relationship between wildfire events and solar electricity generation. To do so, I construct a panel data set that connects monthly solar generation at the census tract level with wildfire smoke density levels overhead. I find that for every microgram of wildfire-related fine particulate matter present in the atmosphere, solar energy production is reduced by 0.014 percent. To provide some context for that number, during wildfire season, a region may be exposed to as much as 2000 micrograms or more in a given month. That level of exposure would result in a 28 percent reduction in solar energy output according to my model. Such major reductions could have huge implications for the future of energy generation and reliability in wildfire prone areas.

1.1 The economic costs of wildfire smoke

The economic consequences of wildfires are often attributed to those impacts which are most visible: charred landscapes, burned-out homes, melted cars, and devastated infrastructure. The costs created by wildfire smoke, however, are often less visible and harder to measure. Smoke plumes can travel hundreds of miles, contributing to poor air quality and negative health outcomes in communities far removed from the fires themselves (Moeltner et. al. (2013); Miller et. al. (2017)). The majority of particulate matter present in wildfire smoke plumes—90 percent by mass—is defined as fine particulate matter, or PM2.5. These particles are less than 2.5 micrometers wide (less than half the size of a red blood cell). Their small size and volatile nature make them particularly effective at causing respiratory and cardiovascular issues (Cascio (2018); Adetona et. al. (2016); Fowler (2003); Reid et. al. (2016); Rappold et. al. (2011); Wettstein et. al. (2018)). Smoke-related PM2.5 exposure is especially dangerous for at-risk groups such as infants, elderly, and those with pre-existing respiratory conditions (Miller et. al. (2017); Holm et. al. (2021); Mccoy and Zhao (2020))

The US Environmental Protection Agency (EPA) already regulates PM2.5 levels as part of the National Ambient Air Quality Standards (NAAQS). These standards were put in place as a way of limiting everyday sources of PM2.5, such as pollution from power plants and automobiles. The addition of wildfire smoke often pushes PM2.5 levels above those allowed by NAAQS (Viswanathan et. al. (2012)). Burke et. al. (2022) found that during smoke events, indoor PM2.5 levels may exceed recommended health levels by 3-4x, and variation from neighborhood to neighborhood can be as high as 20x. Wegesser et. al. (2009) found that not only were PM2.5 levels elevated during smoke events, but that the PM2.5 associated with wildfire smoke was significantly more toxic to lungs than ambient PM2.5 collected outside of the area impacted by smoke.

A number of studies have attempted to quantify the economic impacts of the various health and other issues related to wildfire smoke pollution. Welfare losses stemming from negative health impacts and related losses in labor markets are significant and oftentimes outweigh property losses and suppression spending (Rittmaster et. al. (2006); Kochi et. al.

(2012); Gellman et. al. (2022); Borgschulte et. al. (2022)).

By measuring energy generation losses due to wildfire smoke, I hope to contribute to a more well-rounded understanding of the economic consequences associated with wildfire events. Electricity generation has a very clear economic value and may provide a more concrete example for policy makers of the costs of not responding to growing wildfire prevelance.

1.2 Airborn particulate impacts on solar generation

Solar panels work by collecting sunlight via photovoltaic (PV) cells in the panel. These cells are semiconductors, converting the sunlight's energy into a current that can be directed through the metal contacts in the panel to a converter and eventually onto the grid (or into your home). The efficiency of these panels can be affected by multiple factors, the most obvious being the amount of direct sunlight interacting with each PV cell. Cloud cover, heavy air pollution, and deposits of material on the surface of panels (such as dust, snow, or soot) can reduce the amount of sunlight—also known as irradiance—that reaches a panel, thereby reducing the overall output.

A study of solar radiation levels in China over 55 years (1960 - 2015) found that pollution had reduced solar output potential by 11-15 percent (Sweerts et. al. (2019)). Bergin et. al. (2017) analyzed the impact particulate pollution has had on solar generation across parts of India, China, and the Arabian Peninsula. They found that pollution currently reduces solar generation by 17-25 percent. A similar paper from Son et. al. (2020) tracked particulate matter concentrations and solar output at two different powerplants over the course of 2 years (2015-2017). Over the course of the study, normal levels of PM2.5 pollution reduced solar output by 10 percent. On bad air quality days, pollution reduced output by more than 20 percent.

As mentioned above, wildfire smoke events often significantly exceed normal levels of ambient air pollution. Smoke plumes are composed of thousands of different organic, inorganic, and gaseous compounds. These mixtures are dictated by a number of different factors and therefore vary from fire to fire (Reisen et. al. (2011); Sokolik et. al. (2019); Jeffe et. al. (2020)). Biomass type, moisture, fuel availability, and area burned can all impact the content and amount of smoke released during a wildfire. Biomes that provide ample dry fuel and few barriers to slow a burn, such as grasslands, result in smoke profiles with elevated levels of carbon dioxide, nitrogen, and black carbon. Forests offer an abundance of fuel, but the higher moisture content and density of organic matter result in slower burns and more smoldering, which produces smoke with heavier concentrations of carbon monoxide, hydrogen sulfide, ammonia, and organic carbon aerosols (Akagi et al., 2011; Meinrat O. Andreae Merlet, 2001). Black and organic carbon aerosols are the main causes for light absortion within wildfire smoke plumes (Flowers et. al. (2010); Kirchstetter and Thatcher (2012)).

Some more recent studies have examined the impacts of wildfire smoke on solar energy production and found evidence of significant potential to reduce energy production (Donaldson et al (2021); Bertoletti et al (2022); Keelin et al (2021)).

CHAPTER 2

DATA

For this study, I constructed a panel data set that contains monthly (non-residential) solar generation at the census-tract level in 12 western states: Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Texas, Utah, Washington, and Wyoming. I collected the generation data from the US Energy Information Agency's Open Data Application Programming Interface. Generation data and plant characteristic data had to be collected separately, then matched according to each plant's unique identification number. The data collected spans 8 years, from 2013 through 2020. The location of each power plant in the panel can be seen in 2.1. Plants are color-coded by state and the size of each circle represents differences in generation capacity.

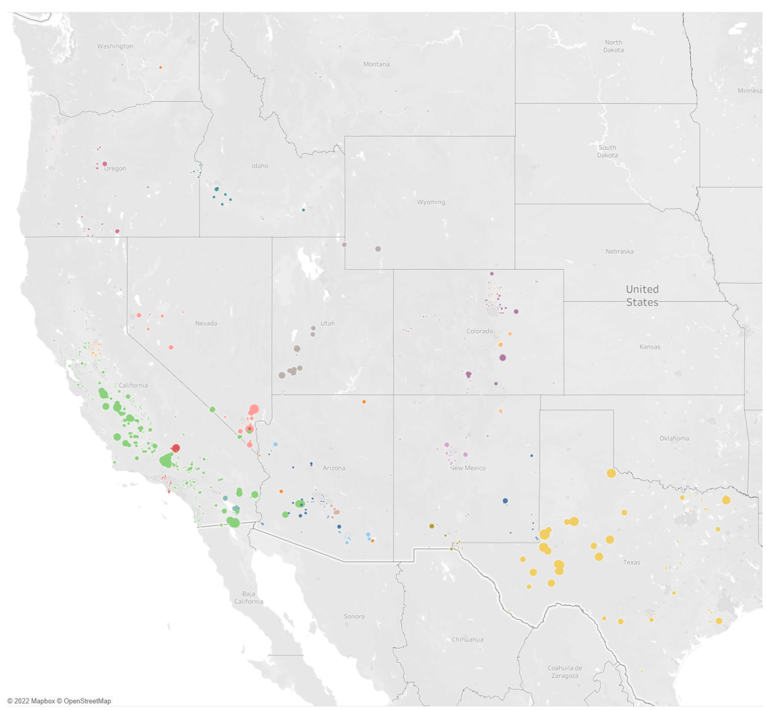

Fig. 2.1: Solar Plant Locations

To measure wildfire smoke density, I rely on a machine learning model developed by Childs et al (2022). The model provides daily wildfire-driven PM2.5 measurements at the census tract level. PM2.5 levels provide a useful measure for wildfire smoke density because the majority of particulate matter in wildfire smoke falls withing the PM2.5 range. PM2.5 levels are also commonly measured at air quality stations across the country, providing a rich source of data to compare against. The model from Childs et al is trained on a combination of ground, satellite, and reanalysis data to isolate smoke PM2.5 levels from pre-existing ambient pollution, allowing me to attribute changes in solar generation to measured PM2.5 levels. I aggregate this daily data to provide total monthly PM2.5 readings for each county in my panel.

Finally, in order to account for various climate characteristics that may affect solar generation, I include data on monthly min and max temperature, precipitation, and average dew point temperature. Differences in ambient air temperature can have a measurable affect on a solar panel's overall output (Peters and Buonassisi (2019)). The average dew point temperature is included as a measure of the relative amount of humidity in a census tract. Increased levels of humidity means more water molecules are present in the air, which can refract light and reduce the amount of sunlight that reaches the panel. Total precipitation should help control for reductions in output from soiling as dust can build up over time on a panel's surface, further reducing energy generation (Bergin et al (2017)). Summary statistics for the panel are shown in 2.1.

Table 2.1: Panel Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
total_gen	35,511	6,722.943	23,145.460	0.270	498,941.000
capacity_mw	35,511	34.138	108.217	0.200	1,396.400
precip	35,511	1.095	1.721	0.000	25.690
tmin	35,511	49.089	14.493	−14.550	86.900
tmax	35,511	75.685	15.846	10.400	112.300
tdmean	35,511	37.947	12.576	−6.775	75.400
smoke_days	35,511	3.326	5.773	0	31
total_pm	35,511	25.208	113.252	0.000	3,705.564
total_gen_norm	35,511	168.034	72.549	0.059	2,929.333

CHAPTER 3

ANALYSIS

For my analysis I use a two-way fixed effect model

$$Y_{it} = \alpha_i + \gamma_t + \beta X_{it} + \epsilon_{it} \tag{3.1}$$

to identify a possible causal relationship between the amount of energy produced each month by solar plants and the total accumulation of wildfire-smoke related PM2.5 in the atmosphere overhead. The use of fixed effects allows me to control for correlations between the regressors and unobserved spatial and temporal effects.

More specifically, I estimate the equation:

$$log(solgen_{it}) = \beta_1 pm_{it} + \beta_2 log(cap_{it}) + \beta_i clim_{it} + census_i + month_t + census * month_{it} + u_{it} \tag{3.2}$$

where $solgen_{it}$ is my dependent variable. Variables pm_{it} and cap_{it} represent the monthly sum of widfire-related PM2.5 and total solar generation capacity, respectively. I use $clim_{it}$ to refer to climate related variables included in the equation as discussed above: maximum and minimum temperature, precipitation, and average dew point temperature. Because total solar generation capacity varies widely from one census tract to another, I normalize both the dependent variable and the total generation capacity with log functions.

The terms $census_i$, $month_t$, and $census * month_{it}$ are the fixed effects terms. Census tract level individual fixed effects should account for time-constant differences between census tracts, such as elevation. Monthly time fixed effects should likewise account for spatially constant differences between tracts. I also include a fixed effect of census tract interacted with each month to account for seasonal variation in solar irradiance in different regions.

Because there is little change from one month or one year to the next for many of these powerplants, there is a high possibility of autocorrelation in the model. To deal with this, I cluster the standard errors at the census tract level.

3.1 Results

Estimates from the fixed effects model are shown in 3.1:

Table 3.1: Regression Estimates

Dependent Variable:	log(total_gen)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	6.794***	4.873***	3.442***			
	(0.0838)	(0.0197)	(0.0659)			
total_pm	7.84×10^{-5}	0.0002***	-0.0002***	-0.0003***	-0.0002***	-0.0003***
	(0.0001)	(2.88×10^{-5})	(3.12×10^{-5})	(2.84×10^{-5})	(2.99×10^{-5})	(3.15×10^{-5})
log(capacity_mw)		1.077***	1.057***	1.049***	1.066***	1.052***
		(0.0061)	(0.0063)	(0.0119)	(0.0058)	(0.0122)
tmin			-0.0221***	-0.0111***	-0.0137***	-0.0117***
			(0.0029)	(0.0015)	(0.0029)	(0.0021)
tmax			0.0331***	0.0251***	0.0144***	0.0126***
			(0.0024)	(0.0012)	(0.0025)	(0.0013)
tdmean			0.0019	0.0054***	-0.0031**	-0.0002
			(0.0012)	(0.0007)	(0.0013)	(0.0011)
precip			-0.0112**	-0.0200***	-0.0112**	-0.0074***
			(0.0048)	(0.0033)	(0.0043)	(0.0027)
Fixed-effects						
geoid				Yes		Yes
month					Yes	Yes
geoid-month						Yes
Fit statistics						
Observations	35,511	35,511	35,511	35,511	35,511	35,511
R^2	2.32×10^{-5}	0.92225	0.94264	0.96422	0.95109	0.97223
Within R^2				0.64845	0.94983	0.61691

Clustered (geoid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

According to the final estimate obtained from column (6), a 1 unit increase in total wildfire-related PM2.5 concentration is correlated with a .0315 percent reduction in solar generation in a given month. That number is difficult to clearly understand without context, so I will highlight a couple of specific examples that illustrate the real-world impact this wildifre smoke is having on solar generation according to the model. To put that into perspective, during the month of September 2020, there was a lot of fire activity in California. That month, parts of Glenn County, CA (northwest of Sacramento) were exposed to roughly 1,540 total micrograms of fire-related PM2.5. That translates to a nearly 22 percent reduction in solar electricity generation that month.

This finding is in line with other similar studies in the literature. Calinou et al (2013) found that aerosol pollution can reduce available solar energy by more than 20 percent, using a model they developed based on clear sky irradiation levels and various aerosol readings. Perry and Troccoli (2015) monitored reductions in solar production caused by a controlled biomass burn near a solar plant in Australia. They observed an overall reduction in solar generation of 7 percent, with a peak reduction of 27 percent. Keelin et al (2021) monitored solar stations during the 2020 fires in California and noted a nearly 6 percent reduction in solar energy output below historical levels at their site in Hanford, CA. Estimates from the California Independent System Operator and Energy Information Institute blame wildfire smoke for reducing California's late summer 2020 solar generation by between 20 and 30 percent.

3.2 Measurement Error

To my knowledge this analysis is the widest ranging panel of data, both in terms of time and scope, used to analyze this issue thus far. Part of my reason for analyzing such a large set of data is the lack of available solar generation data at the daily and hourly level. Wildfires can burn and smolder for weeks on end, continuing to release smoke as they do. But oftentimes smoke-levels are thickest in the hours and days immediately following an ignition. Relying on monthly aggregation to analyze the impacts of these events may cause the analysis to produce a less-than-clear connection between wildfire events and their more immediate impacts on generation.

A majority of solar generation capacity and wildfire events also occur within California. Despite attempts to control for heterskedasticity, autocorrelation, and fixed effects, there may be some omitted variable bias present in not doing more to account for specific state or institutional differences that may also affect generation in response to wilfire events. There may also be unobserved impacts stemming from behavioral differences regarding energy consumption when wildfires occur.

One set of data the model could probably benefit from would be a measure of actual versus expected irradiation reaching the panels. Outside of the precipitation variable, there is not control for cloud cover or other atmospheric variables that may also have an impact on the amount of sunlight reaching the panels.

CHAPTER 4

DISCUSSION

These findings contribute to a growing body of research about the very real threat that wildfires pose to a future of energy production build around solar energy. To my knowledge this is the largest and most diverse panel data set collected and analyzed for the purpose of understanding the relationship between wildfire smoke and solar energy generation. There is a deep body of evidence that exists already which outlines both the harms of wildfire smoke to human health and economic wellbeing, and the impacts of particulate pollution and smoke on solar energy generation.

There is still a lot of room to build on research in this area. In addition to understanding how smoke impacts energy generation, it would be useful to know how consumer behavior around energy consumption changes during wildfire and other extreme weather events. It would seem reasonable to expect energy demand to increase as the bad air quality forces many people inside.

There is also a need for more granular understanding of the day-by-day or hour-by-hour impacts wildfire smoke may have on solar production. Solar output is likely reduced most heavily in the hours and days following a wildfire event, potentially biasing the true size and significance of these reductions downward.

As we seem to be entering a new era of energy production and wildfire devastation, this study and others like it can help inform policymakers and stakeholders about the importance of acknowledging and responding to the risk wildfires pose.